International Journal of Innovation Management
Vol. 22, No. 1 (January 2018) 1850005 (32 pages)

DOI: 10.1142/S1363919618500056

THE EFFECT OF PATH-DEPENDENCE AND UNCERTAINTY ON THE VALUE OF MATURE TECHNOLOGIES

LARS ALKAERSIG[*,§], KARIN BEUKEL[†,¶] and GIANCARLO LAUTO[‡,||]

[*]Technical University of Denmark
Diplomvej 372, 2800 Kgs. Lyngby, Denmark
[†]University of Copenhagen
Rolighedsvej 25, 1958 Frederiksberg, Denmark
[‡]University of Udine
Via Tomadini 30/A, I-33100 Udine, Italy
[§]lalk@dtu.dk
[¶]kab@ifro.ku.dk
[||]giancarlo.lauto@uniud.it

Published 24 April 2017

This paper examines whether technological advances benefit more from path-dependent or path-creating capabilities. Consistently with recent advances in the literature, we argue that multiple technological trajectories can coexist in a field; therefore, firms may contribute to technological development by recombining in novel ways the capabilities that are widespread in the field, or by building novel and rare capabilities. The paper also conceptualises how technological uncertainty affects the value of such capabilities. Using patent data from 1977 to 2007 for firms developing the hydrocracking technology, the paper finds that both rare and widespread capabilities are valuable to the invention process, thereby suggesting that both path-dependent and path-creating strategies are beneficial for technological development. The paper shows that uncertainty has an inverted U-shaped effect on invention value. In particular, under conditions of low uncertainty, path-dependent capabilities tend to be more valuable.

Keywords: Path-dependence; uncertainty; rarity; mature technology; patent value.

Introduction

The evolutionary view of technological change emphasises the coevolution of scientific knowledge and technological capabilities both at the systemic and at the firm level (Nelson and Winter, 1982; Nelson, 1994; Arora and Gambardella, 1994; Metcalfe, 1998). In this approach, path-dependence plays a major role in affecting the diffusion of technologies, by offering increasing returns for the adoption of a given technology — that may be even less performing than competing ones (Arthur, 1989, 1990; David, 1985; Cowan, 1990). The notion of path-dependence has underpinned studies of firm-level innovation of complex technological systems (Cantwell and Bachmann, 1998; Rycroft and Kash, 2002; Guha, 2016) that emphasise the importance of technology design, institutions and organisational networks in shaping the patterns of technology co-evolution. A crucial issue in these conceptualisations concerns how firms can deviate from a well-established trajectory, that is prevalent in an industry, to enter an alternative technological pattern. As Garud and Karnoe (2001) put forward, entrepreneurs pursue 'path creation' by purposefully acting to change the environment in which they are embedded and thus create new paths. Furthermore, Bergek and Onufrey (2013, 2015) have recently proposed an extension of the path-dependence theory arguing that the self-reinforcing mechanisms in place in industries in which multiple technologies exist and interact, allow for the co-existence of multiple technological paths. Also, Suzuki and Methé (2014) found that the effects of path-dependence at firm level vary according to the innovation strategy that a firm pursues, i.e., orientation towards only product or product and process innovation. Therefore, the efforts that individual firms undertake to deviate from a given technological path may generate a variety of persisting technological trajectories.

A crucial question in this debate, that has a straightforward impact on firm strategy, and which remains unanswered, is whether technological advance benefits more from the development of capabilities along an established trajectory (path-dependence) or the initiation of a different one (path-creation). We aim to answer this question by investigating if patents protecting path-dependent inventions contribute more to technological advancement than those protecting path-creating inventions. We characterise path-dependent patents as those arising from a recombination of technologies that are frequently practiced by the firms developing that technology, while path-creating patents are those that exploit rarer technological re-combinations.

To appreciate the relevance of this issue, it is worth noticing that path-creation is a strategic option surrounded by greater uncertainty. The uncertainty that characterises a technology or set of interrelated technologies depends on the dynamics of demand (Fontana and Guerzoni, 2008), the stage of development of the technology and the existence of competing technologies (Ragatz *et al.*, 2002), as well as the rate of change of a given technology in terms of magnitude and pace of improvements (Luque, 2002). Uncertainty tends to increase the value of more frequent recombinations, in particular, because uncertainty tends to increase with technological complexity (Tushman and Rosenkopf, 1992). However, how uncertainty affects the value of path-dependent vs. path-creating technologies remains unanswered. Therefore, the second aim of this paper is to ascertain the moderating effect of technological uncertainty in the relationship between the type of invention (path-dependence vs. path-creating) and invention value.

We use the empirical case of hydrocracking to explore these issues. Hydrocracking is a mature technology widely used in the oil-refining process to transform crude oil into high-value petroleum products. We focused on this technology for three reasons: invention in hydrocracking is based on combinations of technological capabilities that refer to both path-dependent and path-creating trajectories; these advances are often effectively protected by means of patents, which make this technology an ideal context in which to compare path-dependent and path-creating change. Moreover, the degree of uncertainty surrounding this technology has fluctuated, particularly since 1970, and therefore we are able to assess the impact of changes in uncertainty on the patterns of development. Although hydrocracking cannot be considered as representative of the generality of technological dynamics, its development pattern resembles those of many mature technologies and it is, therefore, a relevant case for the understanding of the long-term patterns of technological development. Innovation in energy-related technologies has been found to be particularly prone to path-dependence and lock-in effects (Kalkuhl *et al.*, 2012; Cheon and Urpelainen, 2012).

Consistent with our expectations, the study finds that both kinds of recombinations result in higher invention value and that the relationship between uncertainty and value takes on an inverted U-shape. The benefits of increasing uncertainty are subject to a negative effect, indicating that there is a point at which higher levels of uncertainty become unfavorable. Finally, we find that low uncertainty has a negative moderating influence on the relationship between new path creation and invention value.

This paper contributes to the debate regarding the academic standing of the path-dependence and provides an empirical test of its core propositions that specifies the extent to which path-dependent and path-creating advances contribute to technological development. Specifically, this paper is, to our knowledge, the first to identify degrees of path-dependence at different levels of uncertainty, as key factors for generating valuable inventions and to provide quantitative evidence to support the claims made. This study, therefore, addresses a central issue with respect to the management of innovation, namely, the generation of inventions, and provides insight into the internal and external conditions that support this process. Such insights characterise the features of an environment that is conducive to invention and provide managers with guidance that is relevant to the organisation of research and development (R&D) activities, e.g., by offering an indication of which kind of capability they should develop when facing technological uncertainty.

The remainder of this paper is structured as follows. First, we introduce key theoretical concepts and develop our hypotheses. We then provide an overview of the data and the methodology used, the presentation of our empirical findings and, finally, a discussion of our results.

The Effects of Path-Dependence and Uncertainty on Invention Value

Path-dependence, path creation and the value of firm capabilities

Path-dependence is a critical feature of innovation processes (Arthur, 1989, 1990; David, 1994, Cowan, 1990; Narula, 2002, Martin and Sunley, 2006; Stack and Gartland, 2003) that refers to the fact that actors in innovation systems systematically favor some types of activities in front of alternative ones. This happens because, as a consequence of historical events, they have committed to idiosyncratic investments or because they benefit from network effects. As the process is characterised by self-reinforcing positive feedback and reaction to others' choices (Araujo and Harrison, 2002), it may lock the development of a technology along a given trajectory, especially in contexts in which externalities are strong (Suarez, 2004). Therefore, innovations that are generated within the technological trajectory are more valuable for the system than those generated outside of it, even though alternative technologies could offer a better performance. As a consequence, firms are incentivised to conform to the existing technological trajectory rather than experimenting novel ones. The diffusion of standards such as the QWERTY keyboard and the VHS video recording format are well-known examples of this phenomenon.

While the path-dependence perspective has been fruitful in explaining, ex-post, the diffusion of innovation, it has devoted a more limited attention to the role of agency in affecting the process. To this purpose, a critical issue is to understand how actors may bring to the market an invention that deviates from an established trajectory: the more recent notion of 'path creation' (Garud and Karnoe, 2001; Meyer and Schubert, 2007; Garud *et al.*, 2010) refers to the purposive and creative act of entrepreneurs to breaking technological and cognitive lock-ins by activating a novel network of stakeholders in the innovation system who benefit from the deviating innovation (Sydow *et al.*, 2012). As Agogué *et al.* (2012) put forward, firms face the strategic decision of developing technological capabilities within an already explored trajectory or to explore a novel one; in the latter case, the trajectory may or may not be intelligible to the actors in the field. These three strategies entail the development of different innovation capabilities and are characterised by increasing levels of uncertainty.

The processes of path-dependence and path creation have crucial implications at the organisational level, in terms of both how firms develop their resources and capabilities and how they appreciate their value.

A well-established line of reasoning in the literature on management of innovation conceives innovation as a process of recombination of knowledge concerning the components of a product, or the reconfiguration of product architecture (e.g., Fleming and Sorenson, 2004; Henderson and Clark, 1990). More importantly, firms can reconfigure capabilities with the purpose of generating novel resources (Bowman and Ambrosini, 2003; Beckett, 2016). An expanding knowledge base of specific technological components adds to the technological capability of a firm; furthermore, firms develop capabilities that permit them to combine different technology areas. Increased knowledge of technological components and original re-combinations of these components are sources of technological innovation (Makri *et al.*, 2010).

The path-dependence perspective suggests that firms innovating within a given technological trajectory tend to develop capabilities that are, to a certain degree, similar to each other. Indeed, they share not only the capabilities that are necessary to operate in a given technological area (Winter, 2003), but they are likely to have encountered similar technical problems in the development of the technology (Eisenhardt and Martin, 2000).

A broad diffusion of a capability generates a shared knowledge base that firms in a given industry can exploit through imitation and incremental development because the existence of such a knowledge pool reduces imitation and incremental development capability costs (Aghion and Howitt, 1998). Furthermore, widespread resources and capabilities are consistent with an exploitation strategy, that is conducive to the generation of inventions that are complementary to the existing knowledge base of the firm (Makri *et al.*, 2010, Butler, 1988). In such a setting, homogeneity of capabilities is valuable, because it reinforces the development of the trajectory by offering complementarities to the existing inventions and to the inventions that other actors are developing.

On the other hand, the notion of path creation emphasises the purposeful introduction of novel technological patterns that may eventually give rise to discontinuous innovations. In such a case, firms relying exclusively on the same set of capabilities, especially if they are widely diffused in the competitive environment, are prone to cognitive lock-ins (Leonard-Barton, 1995), and need to develop dynamic capabilities to adjust their existing competence base to changing environmental conditions (Teece *et al.*, 1997; Teece, 2007): in this case also not widely spread capabilities, i.e., rare capabilities are valuable.

The rare capabilities are valuable as they may lead to discontinuous, highly valuable inventions that represent a breakthrough in the field, in a process that resembles path creation: the firm alone, and only alone, can create the invention because it controls the rare capability needed to do so.

For these reasons, two distinct directions for creating valuable inventions are possible to firms: a development of technological capabilities that are widespread in the industry and that have a broad scope of application, or from the creation of rare technological capabilities that may sustain the generation of discontinuous inventions. We argue that the maximum advantage for invention stems from capabilities that are either highly rare or highly widespread in the industry. In fact, these are, respectively, the capabilities that allow a firm to differentiate effectively from its competitors, and those that embody the necessary building blocks for any R&D project regarding the technologies employed in the industry.

We propose the following:

Hypothesis 1: *The rarity/diffusion of an invention has a U-shaped effect on the value of the invention.*

The uncertainty of technological environment and the value of inventions

The process of innovation is influenced by uncertainty and serendipity; therefore, firms cannot predict whether their R&D efforts will succeed in generating an invention, whether such efforts constitute the most efficient strategy for addressing a research dilemma (Ahuja *et al.*, 2008) or whether their investment in the complementary resources necessary to commercialise an invention will be suitable (Storey, 2000; Reitzig, 2006; Zhang *et al.*, 2013). Furthermore, environmental dynamics, depending on the combined effects of market and technological forces (Souder *et al.*, 1998), affect the value of the firm's resource base. Substantial changes in the technological environment, in particular, may cause the obsolescence of a resource, eroding its value (Danneels, 2002). Rarer technological resources are more prone to be associated with a higher degree of uncertainty than less rare technological capabilities (Fleming, 2001).

When a firm can predict the development of technologies and markets, decision making and organisation of R&D are simplified because the interpretation of consumer preferences and competitor strategies requires minimal computational effort. A clear picture of the environmental dynamics permits a firm to focus its R&D efforts on the development of the technological capabilities that are likely to result in marketable inventions. However, in conditions of low uncertainty, there is less opportunity for differentiation because all firms possess shared expectations of technological dynamics (Easterby-Smith, Prieto, 2008). Furthermore, low uncertainty can be characterised by incremental technical change and a decrease in radical innovation (Tushman and Rosenkopf, 1992).

In conditions of high uncertainty, firms establish more sophisticated R&D organisations with effective inter-functional integration (Artz and Brush, 2000; Lai *et al.*, 2010). This approach allows firms to experiment with novel approaches to R&D and to increase or reduce their investment and commitment to specific technology trajectories. In contexts in which it is difficult to assess the relative values of different technology combinations (Ragatz *et al.*, 2002), firms do not tend to follow optimisation criteria in formulating their R&D strategies but, rather, base their decision making on heuristics (Bingham and Haleblian, 2012, Bingham *et al.*, 2007). During periods of uncertainty, firms tend to imitate the innovative decisions and decision-making processes of successful firms, causing innovation models to diffuse quickly across an industry (Ahuja *et al.*, 2008; DiMaggio and Powell, 1983; Westphal *et al.*, 2001).

These two opposing forces suggest that an optimal environment for innovation lays between high and low uncertainty.

Thus, we propose the following:

Hypothesis 2: *The uncertainty of the technological environment in which a firm operates has an inverted U-shaped effect on the value of the invention.*

The effect of environmental uncertainty on the value of rarity of capabilities

This paper aims to provide insight into the effect of uncertainty on the relationship between the rarity/diffusion of technological capabilities on which an invention is built and the value of such invention. Environmental dynamism has a critical role in fostering the processes of knowledge management and renewal of firms' capabilities, including the opportunities for new learning processes (Easterby-Smith and Prieto, 2008). We expect that the potential for a firm to create a valuable invention from either a rare or a less rare combination of technological capabilities is contingent upon the uncertainty that characterises the pattern of evolution of the technology.

In conditions of high uncertainty, irreversible investments in the development of technological capabilities have high opportunity costs. Investments in capabilities that are suitable for a given technological trajectory may lose value if the industry shifts to an alternative technological trajectory. Firms must thus evaluate their commitment to specific technological patterns and compare alternative options; this need for evaluation may lead firms to delay investment decisions and to invest in capabilities that can be exploited in different technological domains (McGrath, 1997; Leiblein, 2003). In these environmental conditions, firms benefitting from widespread technological capabilities appear to have an advantage in adapting to alternative future scenarios, provided such capabilities entail a high degree of generality. However, these environmental conditions also strengthen the value of rarer capabilities; the future development of technologies can make intensive use of specific combinations of technological resources and capabilities, the value of which is increased compared to alternative combinations of capabilities (Damanpour and Schneider, 2006). The actual value of resources and capabilities under high uncertainty is difficult to predict; however, it can be argued that rare resources and capabilities benefit from increased uncertainty.

By contrast, under conditions of low uncertainty, the values of rare and widespread capabilities change. A clear competitive and technological pattern of demand reduces the risks associated with the development of unique capabilities (Sorenson, 2000), including the investment in widespread capabilities. In this context, a broader range of technological capabilities is useful in generating inventions rather than only those capabilities at the extremes of the distribution, i.e., those capabilities that are either especially unique or especially widespread in the industry.

For this reason, we propose the following:

Hypothesis 3a: *The relationship between the value of an invention and its rarity/diffusion is moderated by low uncertainty, thus flattening the U-shaped relationship.*
Hypothesis 3b: *The relationship between the value of an invention and its rarity/diffusion is moderated by high uncertainty, thus sharpening the U-shaped relationship.*

Research Design

Research setting

The unit of analysis in our study is thus the individual invention, operationalised as a patent. We acknowledge that patents are an imperfect proxy for inventions, as many inventions are not patentable or are purposely kept secret; however, this approximation is very often accepted in the literature (e.g., Mastrogiorgio and Gilsing, 2016; Bertoni and Tykvová, 2015; Arora *et al.*, 2016). Firms developing the technology at the center of our investigation, i.e., hydrocracking, do not present a more pronounced tendency to protect their inventions by means of secrecy than in other technologies, and therefore the use of patents as a proxy for inventions seems appropriate.

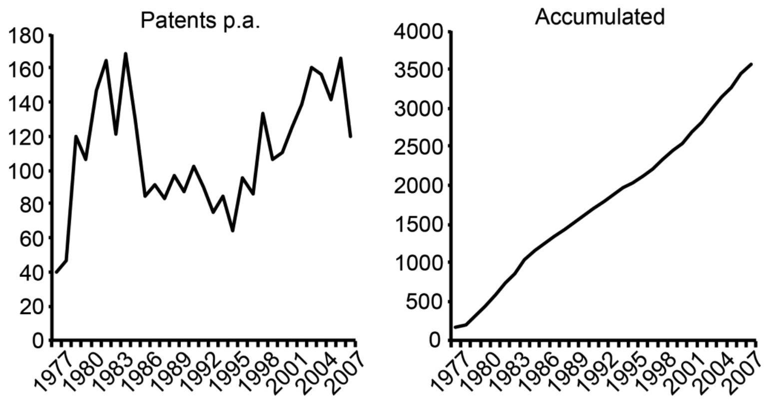

Fig. 1. Annual hydrocracking patent applications and accumulated hydrocracking patents.

This study draws upon a unique dataset comprising all the patent applications that pertain to hydrocracking technology. Patents represent the applied research outcomes within the industry (Meyer, 2000). A patent is at the same time a firm resource and an expression of a firm's technological capabilities (Trajtenberg, 1990).

Hydrocracking is a technology applied at the later stages of the oil-refining process; it utilises a process of catalytic cracking to convert heavy hydrocarbons into higher value-added, lower molecular weight compounds under hydrogen pressure (Billon and Bigeard, 2001). This technology thus increases the value of refinery output through the conversion of lower value petroleum products, such as lubrication oils, into higher value products, such as jet fuel. Although this is a mature technology originally developed in 1927, its continued application in modern refineries ensures that the technology is continuously developed.

Figure 1 presents patents applied for on an annual basis and the accumulated number of patents protecting this technology. It is clear that patenting has highs and lows, respectively in 1983 and 1998, and 1979, 1992 and 2006. These fluctuations indicate that the technology is a suitable candidate for an uncertainty study (Cheon and Urpelainen, 2012).

Data

In this study, we focus on patent applications as they express the inventive activity around, and the interest of firms for, a given technology; other relevant measures, such as granted patents would express a dimension of the quality of the inventions (Ernst, 2003), which is not directly related to the dynamics of path-dependence and path-creation that are at the core of this study, and which anyhow we capture with a more sophisticated measure of value. We classify patent applications in our dataset into distinct technology areas that are characteristic of hydrocracking. Combinations of these classifications are used to indicate whether a patent builds upon a bundle of more than one technology area. Thus, we can identify how rare a given technological combination underlying an invention is at a given time.

The use of patent data to explore technology combinations has predominantly relied on International Patent Classification (IPC) codes to identify the technological scope of a patent, although prior studies have found discrepancies with respect to this measure, in particular, because some technology areas are covered by different sections of the IPC (Cohen *et al.*, 2002; Harhoff *et al.*, 2003; Lerner, 1994).

To address these issues, we offer an alternative to the use of IPC classes to determine the technological scope of a patent. This new approach groups the IPC codes according to their technological applications through a qualitative process that involves a technical field expert.

With the aid of this expert, we identified three distinct technology areas within hydrocracking. *Process technologies* (which we term ‘A’) are primarily associated with the integration of the hydrocracking process into the overall refining process. Area A, therefore, includes technologies that are involved in the flow of petroleum-based liquids, such as valves, pipes and associated controllers. *Catalyst preparation* (which we term ‘B’) concerns the manufacturing process of the catalyst needed for hydrocracking to occur. This category includes both the manufacture of the carrier of the catalyst (the base to which the active component in the catalyst is applied) and the application of the active component to the carrier in the manufacturing process. The area of *feeds and products* (which we term ‘C’) is concerned with the chemical nature of the raw materials of the refineries (feeds) and the chemical reactions that convert specific feeds into specific products.

We also considered the combinations between these three elementary technology areas, obtaining a sevenfold classification.[1] For example, patents that combine the development of the active component (C) with the manufacturing technology (B) are common (BC).

Each area is associated with a group of relevant IPC codes, summarised in Table 1. The search on Derwent was performed for patent applications in the time range 1977–2007 that matched the IPC classes mentioned in the column “Associated IPC classes”, with the exception of those in the “Excluded IPC classes”. The Table highlights that some IPC codes that are similar to one another in the classification scheme may cover alternative applications or competing technologies.

[1]A combination of different technology areas is based on the nature of the invention and the utilised technologies, not on the patent claim itself.

Table 1. Hydrocracking technology areas and IPC classes.[a]

Technology area	Associated IPC classes	Excluded IPC classes	Percentage of observations
Process technologies (A)	C10G-065/00 B01J-008/00		5%
Catalyst preparation (B)	B01J-021/00 to B01J-049/00	B01J-023/76 B01J-029/00	21%
Feeds and products (C)	C10G-045/00 C10G-047/00 C10G-049/00	C10G-045/44 C10G-045/54 C10G-045/58 C10G-047/24-30	8%
AB	Combinations of above classes		4%
AC			13%
BC			37%
ABC			11%

[a]IPC classes ending in /00 signify that all nine-digit subclasses within the seven-digit class are included unless otherwise noted.

For instance, the IPC subclasses C10G-47/24-30 are excluded from C because they constitute a technology that competes with hydrocracking and that is entirely different from, and cannot be compared to, the hydrocracking process. Such issues are difficult to identify through quantitative methods because different IPC codes often share the first seven of nine digits in the IPC coding scheme, making it difficult to positively identify technological proximity without expert advice.

Each patent in our sample is classified according to one or more of these technology areas.

Our sample consists of 3,902 patents from 1977 to 2007 that were collected from the Derwent Innovation Index. This time window has been selected to minimise the effect of macroeconomic shocks on R&D budgets and on inventive activity of firms operating in the petroleum industry, such as the 1973 oil crisis and the financial crisis of 2008. We identified 26 firms with five or more patents from this period from the assignees of these patents and for which we have collected firm-level data. This process yielded a data set of 2,416 patents associated with these firms, with the remaining patents assigned to individuals, universities or firms with fewer than five hydrocracking patents. To obtain a measure of patent value, we linked our patent data to the OECD 2010 citations database (Webb *et al.*, 2005), which contains citation data for all patents filed at the World Intellectual Property Organization and at the European Patent Organization. After excluding patents that are not listed in this database, we obtain a valid dataset of 934 patents. This means that the patents that were only applied in one country, e.g., China did not enter into the estimations. Recent research shows that a majority of patents are only applied locally (Alcacer *et al.*, forthcoming), why this decrease in number of patent families does not come as a surprise, but is merely an artifact of the way we gathered the patent data, that is not presented in other studies, that starts by only searching US or EPO patent families for a given technology. The bias is therefore towards large international firms, which our sample is also confirming (i.e., those with more than five patent application families available in the citations database provided by EPO).

Variables

Building on an extensive literature that relates the value of inventions to the value of patents (e.g., Trajtenberg, 1990; Hall *et al.*, 2005), we adopt a patent-based measure of value. While most measures of patent value rely predominantly on forward citations (van Zeebroeck and van Pottelsberghe de la Potterie, 2011; Gambardella *et al.*, 2008), we adopt a multidimensional conceptualisation that captures both technological significance and market value, following Lanjouw and Schankerman (2004). Our dependent variable (Pat_Val) combines two measures: standardised technological importance (expressed by forward citations) and standardised geographical scope (expressed by family size). Patent value is therefore defined as follows:

$$\text{Pat\_Val} = \text{st(forward citations)} + \text{st(family size)}.$$

We normalise the variable before using it in the estimations.

The first explanatory variable under consideration expresses the *rarity/diffusion* of a patent in a technology field.

We measure the rarity of a given patent as the ratio of the number of patents described by the technology area to which they refer to through the given year to the total number of registered patents. Rarity is defined as one minus this ratio.

$$1 - \text{RARITY OF INVENTION} = 1 - \frac{\sum \text{Patent type}, t_n}{\sum \text{Patents types in industry}, t_n}.$$

Because we assume a curvilinear relationship between rarity and patent value, we also include a squared term for this variable in our regression models.

We found inspiration for this variable in the measure of path-dependence by Song *et al.* (2003). They operationalise path-dependence as "*the ratio of the number of self-citations to the number of total citations made by a* [...] *firm in each patent technology class*" (p. 358). However, this measure focuses on path-dependence at the firm level, i.e., the extent to which the firm is innovating by building on it existing capabilities vs. introducing a new firm-level trajectory. Our focus is slightly different, as it concerns the contribution of an invention to an existing technology vs. creation of a trajectory that is new for all the firms developing the hydrocracking technology.

Therefore, we built on the notion that path-dependence is expressed by the reproduction of an existing technological capability (i.e., self-citation in Song *et al.*'s approach), but we translated it into a measure of "rarity", that is more suitable to capture deviation from a trajectory at technology field level.

The other key explanatory variable is technological *uncertainty*. As our focus is on the rate of change of a given technology along its trajectory — rather than sources of uncertainty associated with the demand or with the emergence of alternative technologies — we follow the approach suggested by Luque (2002), and applied in various studies (e.g., Park *et al.*, 2012), which considers the annual variation rate in patents in a given industry or relative to a given technology. Because patents denote dynamic change, a negative value of the measure is related to less frequent change and therefore low levels of uncertainty. In the formula

$$\Delta P_{it-(t-1)=\frac{\mathrm{NP}it-\mathrm{NP}i(t-1)}{\mathrm{NP}i+\mathrm{NP}i(t-1)/2}}$$

the term $\Delta P_{it-(t-1)}$ represents the percentage change in the number of patents protecting a technology i at time t, and NP_{it} is the number of patents assigned to technology i at time t.

Because we assume a curvilinear relationship between uncertainty and patent value, we also include a squared term for this variable in our regression models. The unit of observation is each patent that is assigned to the firm; the focal patent is therefore added to the denominator and the numerator. Based on this variable, we generate two binary variables, Low_Uncertainty and High_Uncertainty that take the value of 1 when uncertainty is one standard deviation below and one standard above the mean.

We apply firm-specific and patent-specific controls.

At the firm level, control variables are included for the firm size and operationalised as the number of employees, and for the degree of firm internationalisation, control variables are operationalised as the number of branch locations. We gathered these data from the ORBIS database. We include these controls because our data cover both large, fully integrated oil firms and smaller, more narrowly focused firms. We control *experience* as a measure of the total number of hydrocracking patents that have been applied for. The degree of *firm specialisation* is defined as the extent to which a firm has more patents within a single technology area, or a combination of technology areas, than more than 90% of firms. This variable changes over time, to account for the accumulation of patents in different technology areas. We also control prior specific experience accumulated in specific patent types. This variable is represented by the number of patents of a specific type in $t-1$ as a share of the total accumulated hydrocracking patents in the firm in $t-1$.

At the patent level, several control variables are included. The age variable indicates the number of years since patent application. To control input from scientific sources, a dummy variable that measures whether the focal patent cites non-patent-related literature is included. We also control the number of inventors in addition to the number of assignees. Other measures that indicate the patent value is whether the patent is granted and if the patent has been opposed.

Analytical strategy and descriptive statistics

The empirical study is conducted in three stages: first, we explore the relationship between invention value and technological rarity/diffusion; we then consider the effect of uncertainty; and, finally, we explore the moderating effects of low- or high-uncertainty environments on the relationship between technological rarity and invention value.

The dependent variable in these models (Pat_Val) is censored because it is the product of standardised forward citations and standardised family size, with values

Table 2. Descriptive statistics.

Variable	Mean	Std. Dev.	Min	Max
Patent value	0.001	1.446	−1.988	151.154
Forward citations	3.124	6.155	0	95
Family size of patent	1.073	7.253	0	111
1-Rarity of invention	0.465	0.254	0.029	1
1-Rarity of invention (sq)	0.281	0.238	0.0008	1
Uncertainty of environment	0.149	0.541	−1.259	2
Uncertainty of environment (sq)	0.315	0.418	0.0015	4
Low uncertainty (dummy)	0.111	0.314	0	1
Non-patent related citations (dummy)	0.085	0.280	0	1
Specialised firm	0.200	0.400	0	1
Experience	0.546	0.838	−16	1
Internationalisation	1.435	1.814	0	6.302
Firm size	8.004	368.987	0	1.171
Patents age	1.380	7.774	0	29
Experience on the technology	6.620	6.511	1	246
Patent grant	0.602	0.489	0	1
Patent opposition	0.009	0.097	0	1
Number of inventors on patent	4.585	4.326	1	74
Number of assignees on patent	1.841	0.954	1	10

Table 3. Correlation matrix.

		1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19
1	Patent value	10.000																		
2	Forward citations	0.7228	10.000																	
3	Family size of patent	0.7227	0.0447	10.000																
4	1-Rarity of invention	−0.0190	0.0862	−0.1136	10.000															
5	1-Rarity of invention (sq)	−0.0013	0.1129	−0.1147	0.9687	10.000														
6	Uncertainty of environment	0.0760	0.1223	−0.0124	0.0772	0.0958	10.000													
7	Uncertainty of environment (sq)	0.0140	0.1297	−0.1095	0.1473	0.1797	0.5572	10.000												
8	Low uncertainty (dummy)	−0.0337	−0.0130	−0.0357	0.0108	0.0176	−0.5095	0.1042	10.000											
9	Non-patent-related citations (dummy)	0.0947	0.0367	0.1002	0.1075	0.0854	−0.1185	−0.0443	0.0254	10.000										
10	Specialised firm	0.0119	0.0277	−0.0105	0.0041	−0.0025	−0.0342	−0.0342	−0.0495	−0.0671	10.000									
11	Experience	−0.0342	−0.1042	0.0549	−0.3734	−0.4022	−0.0857	−0.3246	−0.0175	−0.0705	−0.0083	10.000								
12	Internationalisation	0.0237	0.0428	−0.0086	0.0842	0.0897	−0.0447	−0.0610	−0.0331	0.0444	0.1627	−0.0539	10.000							
13	Firm size	0.0550	0.0037	0.0758	0.0072	0.0211	−0.0076	−0.0061	−0.0470	0.0698	−0.2490	−0.0979	0.2787	10.000						
14	Patents age	0.1172	0.3063	−0.1370	0.2542	0.2912	0.3304	0.4824	0.0837	−0.0500	−0.0767	−0.2077	0.0485	0.0365	10.000					
15	Experience on the technology	−0.0798	−0.1662	0.0508	−0.2217	−0.2208	−0.0885	−0.1843	−0.0183	−0.0338	−0.2370	0.1659	−0.3557	0.0144	−0.4670	10.000				
16	Patent grant	0.3183	0.1799	0.2802	0.0311	0.0346	0.1780	0.1715	0.0369	0.0295	0.0289	−0.0476	−0.0434	−0.1033	0.4176	−0.2524	10.000			
17	Patent opposition	0.0956	0.0123	0.1260	−0.0112	−0.0231	−0.0128	−0.0280	−0.0349	0.0090	0.0328	0.0032	0.0194	−0.0368	−0.0399	0.0320	0.0801	10.000		
18	Number of inventors on patent	0.3283	−0.0097	0.4842	−0.0419	−0.0583	−0.1047	−0.1645	−0.0291	0.0921	0.0052	0.0487	−0.0823	0.0016	−0.3096	0.2117	−0.0191	0.0449	10.000	
19	Number of assignees on patent	0.1495	−0.0566	0.2728	−0.0159	−0.0350	−0.1002	−0.1915	−0.0482	0.1390	0.0214	0.0551	−0.0475	0.1719	−0.3365	0.0722	−0.0431	0.0508	0.3038	10.000

Table 4. OLS regression with patent value as the dependent variable.

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
1-Rarity of invention		−1.983***		−2.026***	−2.353***	−2.128***
		[0.291]		[0.293]	[0.321]	[0.711]
1-Rarity of invention (sq)		1.778***		1.799***	2.175***	1.901**
		[0.379]		[0.380]	[0.390]	[0.760]
Uncertainty of environment			0.186**	0.194**		
			[0.071]	[0.075]		
Uncertainty of environment (sq)			−0.231	−0.261*		
			[0.144]	[0.132]		
1-Rarity of invention* Low uncertainty (dummy)					2.868**	
					[1.114]	
1-Rarity of invention (sq)* Low uncertainty (dummy)					−3.035***	
					[0.980]	
Low uncertainty (dummy)					−0.641**	
					[0.245]	
1-Rarity of invention* High uncertainty (dummy)						0.640
						[2.189]
1-Rarity of invention (sq)* High uncertainty (dummy)						−0.587
						[1.921]
High uncertainty (dummy)						0.051
						[0.551]
Non-patent-related citations (dummy)	0.229	0.284*	0.257	0.315*	0.302*	0.294*
	[0.160]	[0.164]	[0.164]	[0.168]	[0.168]	[0.168]
Specialised firm	0.063	0.056	0.066	0.059	0.050	0.043
	[0.104]	[0.105]	[0.102]	[0.104]	[0.105]	[0.111]

Table 4. (*Continued*)

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Experience	−0.003	−0.022	−0.027	−0.052	−0.021	−0.028
	[0.083]	[0.082]	[0.081]	[0.079]	[0.082]	[0.085]
Internationalisation	0.028	0.028	0.025	0.025	0.027	0.031
	[0.043]	[0.043]	[0.041]	[0.041]	[0.043]	[0.042]
Firm size	0.022	0.020	0.022	0.019	0.018	0.019
	[0.014]	[0.014]	[0.014]	[0.015]	[0.015]	[0.015]
Patent age	0.026***	0.026***	0.027**	0.027**	0.026***	0.020**
	[0.009]	[0.009]	[0.010]	[0.010]	[0.009]	[0.008]
Experience on the technology	−0.000	−0.001	−0.000	−0.001	−0.000	−0.001
	[0.001]	[0.001]	[0.001]	[0.001]	[0.001]	[0.001]
Patent grant	0.794***	0.782***	0.778***	0.763***	0.789***	0.784***
	[0.066]	[0.065]	[0.069]	[0.068]	[0.064]	[0.061]
Patent opposition	0.895	0.939*	0.895*	0.939*	0.926*	0.941*
	[0.530]	[0.528]	[0.527]	[0.524]	[0.537]	[0.530]
Number of inventors on patent	0.117***	0.118***	0.117***	0.118***	0.118***	0.118***
	[0.028]	[0.029]	[0.028]	[0.029]	[0.029]	[0.030]
Number of assignees on patent	0.128**	0.135**	0.122**	0.130**	0.135**	0.132**
	[0.061]	[0.061]	[0.059]	[0.059]	[0.059]	[0.061]
Constant	−1.840***	−1.381***	−1.772***	−1.293***	−1.305***	−1.292***
	[0.211]	[0.223]	[0.218]	[0.230]	[0.226]	[0.219]
R-squared	0.244	0.253	0.248	0.257	0.256	0.255
Adj. R-squared	0.235	0.242	0.237	0.245	0.243	0.242
No. of obs.	934	934	934	934	934	934
F test	67.779***	156.989***	61.5932***	153.575***	137.271***	169.354***

Note: *$p < 0.1$, **$p < 0.05$, ***$p < 0.01$.

ranging from −1.989 to 15.115. Although a Tobit model is appropriate for censored data (Wooldridge, 2009), we rely on OLS estimations because only four observations were present at the lowest value and the variable has no upper bound. The model can be written as follows:

$$\mathrm{Pr(PAT\_VAL)} = rr^2, u, u^2, r^*u_{\mathrm{low/high}}, r^{2*}u_{\mathrm{low/high}}, u_{\mathrm{low/high}}, c,$$

where the probability of generating high-value patents (PAT_VAL) depends on the ratio of rarity (r) and of rarity squared (r^2), the ratio of uncertainty (u) and of uncertainty squared (u^2), a dummy for low uncertainty (u_{low}), a dummy for high uncertainty (u_{high}) and control variables (c).

Descriptive statistics are presented in Table 2, and correlations are presented in Table 3. Table 2 shows that the explanatory variable rarity of inventions ranges between 0.03 and 1, with a mean of 0.465 and a standard deviation of 0.254, which indicates that the data points are dispersed over the range of possible outcomes. We observe significant environmental change over time: the uncertainty variable, which ranges from −1.259 to 2, with a mean of 0.150 and a standard deviation of 0.542 (indicating high variance).

Table 3 presents pairwise correlations. The low correlation (0.04) between the two patent value indicates forward citations and family size indicates that the two measures express different dimensions of value. The low maximum level of correlation between variables, and the Variance Inflation Factor lower than 10, allow us to rule out that the results of the regressions are biased by collinearity issues. We performed a robustness analysis, taking each of these indicators individually into account, to verify the results of the measure we propose for patent value.

Results

Our analytical strategy consists in the examination of the hypotheses of the study by means of a series of regression models addressing the effects of rarity and uncertainty. Subsequently, we assess the robustness of these findings by adopting a different specification of the dependent variable.

Table 4 presents our main regression results; all Models 1–6 are significant and have R-square of approximately 0.25, which shows that they explain a substantial part of the variance. Model 1 is the baseline model and includes only the controls; Models 2 and 3 separately examine the effects of rarity and uncertainty, whereas Model 4 presents the fully specified model; finally, Models 5 and 6 consider the interaction between rarity and low and high uncertainty, respectively.

We begin our analysis by addressing Hypothesis 1, which states that the relationship between the value of an invention and its rarity is curvilinear and takes a

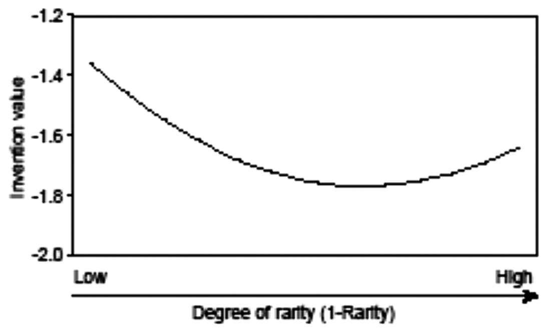

Fig. 2. Graphical plot of a U-shaped relationship between 1-Rarity and patent value.

U-shape. Model 4 demonstrates that both the linear and the squared terms for rarity are significant, the former taking a negative sign and the latter a positive sign. This finding indicates a U-shaped relationship between rarity and patent value, as graphically depicted in Fig. 2. This result is consistent with Model 2, which considers the effect of rarity alone.

These results support Hypothesis 1 and indicate that highly valuable inventions build on either rare or less rare technological capabilities.

Model 4 also provides support for Hypothesis 2, indicating that the relationship between the value of an invention and uncertainty is curvilinear and takes an inverted U-shape, as the graphical representation in Fig. 3 shows. Both the linear and the squared terms for uncertainty are significant, taking positive and negative signs, respectively. We find partial support for this result in Model 3, in which the quadratic term is slightly above the 10% significance threshold. This finding indicates that only a moderate level of technological dynamism is beneficial for the value of inventions.

The models demonstrate that the optimal environmental conditions for the development of valuable inventions are conditions of moderate uncertainty.

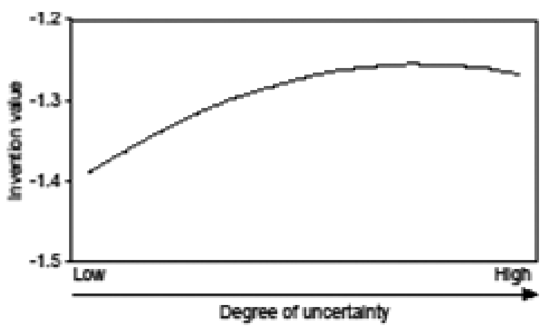

Fig. 3. Graphical plot of an inverted U-shaped relationship between uncertainty and patent value.

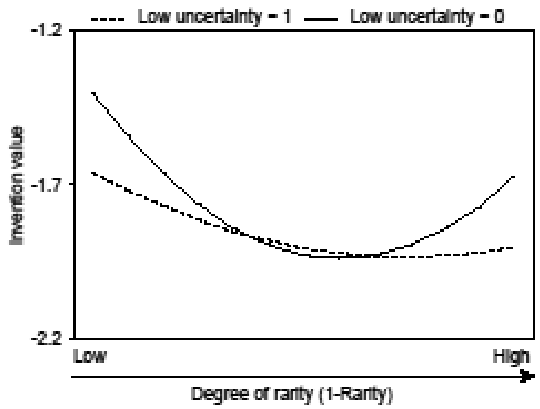

Fig. 4. Graphical plot of an inverted U-shaped relationship between uncertainty and patent value, moderated by low uncertainty.

Models 5 and 6 provide insight into the drivers of value when uncertainty takes values outside the optimal zone of moderate uncertainty. Whereas conditions of high uncertainty (Model 6) do not affect the relationship between rarity and patent value, we find statistically significant moderating effects of low uncertainty (Model 5). Figure 4 graphically presents the change in the relationship as a flattening of the curve, providing support for Hypothesis 3a but not supporting Hypothesis 3b.

With respect to the controls, the models consistently show that patents that rely on scientific knowledge have multiple inventors and have been granted and faced an opposition are associated with a high value.

Robustness Checks

To validate the reliability of our findings, the models presented in Table 4 consider both robust and clustering standard errors. The results (not included but available from the authors) resemble those shown in Table 4; however, the uncertainty of environment squared is also significantly negative in Model 3.

We also replicate the analyses (not included but available from the authors) by using modified versions of the variable expressing the rarity of a patent, which in the main models was calculated with reference to a one-year time window. These modified versions of the rarity variables considered the ratio between the number of patents in a given technology area and the total number of registered patents in the most recent two-, three- and five-years. The findings are robust across all estimates; coefficients are lower in the models including the 5-years lagged variable, while the inclusion of the 2- and 3-years lagged variable are unchanged. Overall, these models strengthen the findings of the main models.

Table 5. Tobit regression with patent value as the dependent variable.

	Model 7	Model 8	Model 9	Model 10	Model 11
1-Rarity of invention		−1.996*** [0.270]	−2.053*** [0.264]	−2.350*** [0.310]	
1-Rarity of invention (sq)		1.795*** [0.314]		1.825*** [0.316]	2.166*** [0.347]
Uncertainty of environment			0.213*** [0.075]	0.223*** [0.078]	
Uncertainty of environment (sq)			−0.282* [0.146]	−0.314** [0.130]	
1-Rarity of invention*Low uncertainty (dummy)					2.721** [1.061]
1-Rarity of invention (sq.)* Low uncertainty (dummy)					−2.822*** [0.969]
Low uncertainty (dummy)					−0.654*** [0.252]
Non-patent-related citations (dummy)	0.229 [0.163]	0.285* [0.164]	0.262 [0.164]	0.321* [0.165]	0.303* [0.167]
Specialised firm	0.063 [0.093]	0.055 [0.098]	0.067 [0.092]	0.060 [0.099]	0.050 [0.099]
Experience	−0.004 [0.061]	−0.022 [0.062]	−0.033 [0.054]	−0.058 [0.054]	−0.022 [0.062]
Internationalisation	0.029 [0.026]	0.029 [0.026]	0.025 [0.026]	0.025 [0.025]	0.028 [0.026]
Firm size	0.021 [0.014]	0.019 [0.014]	0.021 [0.014]	0.018 [0.014]	0.017 [0.014]

Table 5. (*Continued*)

	Model 7	Model 8	Model 9	Model 10	Model 11
Patents age	0.026***	0.026***	0.028***	0.029***	0.027***
	[0.007]	[0.007]	[0.008]	[0.008]	[0.007]
Experience on the technology	−0.000	−0.001	−0.000	−0.001	−0.000
	[0.001]	[0.001]	[0.001]	[0.001]	[0.001]
Patent grant	0.794***	0.782***	0.775***	0.760***	0.788***
	[0.063]	[0.061]	[0.065]	[0.062]	[0.059]
Patent opposition	0.894	0.939*	0.895*	0.939*	0.923*
	[0.543]	[0.539]	[0.539]	[0.534]	[0.546]
Number of inventors on patent	0.117***	0.118***	0.117***	0.118***	0.118***
	[0.023]	[0.024]	[0.023]	[0.023]	[0.024]
Number of assignees on patent	0.132**	0.139**	0.126**	0.133**	0.139**
	[0.063]	[0.062]	[0.061]	[0.060]	[0.061]
Constant	−1.852***	−1.391***	−1.774***	−1.289***	−1.314***
	[0.139]	[0.148]	[0.153]	[0.161]	[0.154]
Sigma Constant					
	1.262***	1.255***	1.258***	1.251***	1.252***
	[0.011]	[0.011]	[0.010]	[0.010]	[0.011]
No. of obs.	934	934	934	934	934
Uncensored obs.	930	930	930	930	930
Log likelihood	−1543.876	−1538.26	−1.540.763	−1.534.642	−1536.28
Pseudo R-squared	0.078	0.082	0.080	0.084	0.083
F test	439.726***	399.196***	362.471***	279.856***	460.980***

Note: $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table 6. Negative binomial regression with forward citations as the dependent variable.

	Model 12	Model 13	Model 14	Model 15	Model 16
1-Rarity of invention		−2.058***		−2.017***	−2.744***
		[0.334]		[0.331]	[0.357]
1-Rarity of invention (sq)		2.029***		1.913***	2.825***
		[0.408]		[0.414]	[0.430]
Uncertainty of environment			0.198**	0.201**	
			[0.101]	[0.099]	
Uncertainty of environment (sq)			−0.408***	−0.418***	
			[0.131]	[0.126]	
1-Rarity of invention* Low uncertainty (dummy)					5.603***
					[1.967]
1-Rarity of invention (sq)* Low uncertainty (dummy)					−6.596***
					[1.979]
Low uncertainty (dummy)					−0.835**
					[0.416]
Constant	−0.582*	−0.124	−0.531*	−0.061	−0.036
	[0.315]	[0.334]	[0.309]	[0.326]	[0.322]
Ln alpha					
Constant	0.132**	0.111	0.120*	0.098	0.092
	[0.067]	[0.070]	[0.070]	[0.074]	[0.070]
Pseudo LL	−1.962.886	−1.957.758	−1.958.934	−1.953.643	−1.952.594
No. of obs.	934	934	934	934	934
Wald-Chi^2	642.6914***	1336.384***	793.2447***	1913.349***	2094.292***

Note: $^*p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table 7. Negative binomial regression with family size as the dependent variable.

	Model 17	Model 18	Model 19	Model 20	Model 21
1-Rarity of invention		−0.551***		−0.574***	−0.501***
		[0.168]		[0.168]	[0.181]
1-Rarity of invention (sq)		0.308*		0.322*	0.224
		[0.162]		[0.166]	[0.172]
Uncertainty of environment			0.083**	0.089***	
			[0.035]	[0.031]	
Uncertainty of environment (sq)			−0.106*	−0.124**	
			[0.059]	[0.058]	
1-Rarity of invention*Low uncertainty (dummy)					−0.425
					[0.464]
1-Rarity of invention (sq)*Low uncertainty (dummy)					0.688
					[0.471]
Low uncertainty (dummy)					−0.033
					[0.471]
Constant	1.798***	1.972***	1.826***	2.011***	1.971***
	[0.087]	[0.092]	[0.084]	[0.087]	[0.089]
Ln alpha					
Constant	−2.334***	−2.371***	−2.348***	−2.387***	−2.376***
	[0.353]	[0.361]	[0.353]	[0.361]	[0.361]
Pseudo LL	−2672.592	−2662.187	−2669.193	−2657.988	−2660.929
No. of obs.	934	934	934	934	934
Wald-Chi^2	2122.063***	3003.254***	2369.501***	2908.646***	3645.035***

Note: *$p < 0.1$, **$p < 0.05$, ***$p < 0.01$.

To further validate the reliability of our findings, we specified a series of Tobit estimations. The results (which do not consider the interaction between high uncertainty and rarity) are presented in Table 5. We applied to these results the tests proposed by Wiersema and Bowen (2009) and Bowen (2012) (results not presented here) and found that they are consistent with the results of our principal model.

To further address issues associated with the use of a composite-dependent variable, we ran all models individually with both forward citations and family size as the dependent variables. Table 6 presents the results of negative binomial regression models (Models 12 to 16), where the dependent variable is the number of forward citations, showing that the key explanatory variables maintain their signs and significance levels.

Table 7 (Models 17 to 21) also shows the results for all specifications, utilising only the count of family size as the dependent variable. The results were significantly different when we analysed the moderating effects in Model 20. Whereas all the results for controls were consistent with the main results, the results for the interaction became insignificant, and the signs of the coefficients were the opposite of those in our main results and in the results that only took forward citations into account. This finding might indicate that, during periods of low uncertainty, the family size measure as the dependent variable is less reliable because this indicator is firm-driven.

Additionally, tests of different specifications of specialised firms were conducted. In our main models, we used a measure of whether the firm behind an invention is specialised in terms of its patent portfolio relative to the majority of the population of firms, where the majority of the firm population is defined as 90% of firms. In robustness checks, we used two other specifications of specialisation: a specification in which the majority is defined as 75% of the firm population and a specification in which the majority is defined as the mean plus one standard deviation. Employing these specifications, the results remained unaffected.

Concluding Remarks

This study theorised and examined a central research question: under what conditions do capabilities developed within and outside a path-dependent trajectory contribute to invention value? We investigated the relationship between the path-dependence and capability and ability of a firm to generate a valuable invention.

In our analysis, we found evidence beyond a certain point of positive returns from widespread capabilities, referring to the value generated by a path-dependent process. This finding indicates that the capabilities that are idiosyncratic to a firm, in addition to the capabilities that are widely diffused in a technological field, lead to superior value. These results provide empirical support for the core theoretical proposition that the path-dependent replication of existing patterns of activity carries higher systemic value. This paper provides evidence of this phenomenon in the context of development of patentable inventions, thereby those resulting from path dependent recombination process contribute more to the further development of the technology by other factors.

This paper also demonstrates that an optimum level of uncertainty permits firms to generate valuable inventions, in accordance with the insights of previous authors (e.g., Bingham and Haleblian, 2012; Bingham *et al.*, 2007; Ragatz *et al.*, 2002). Our data show that conditions of both low and high uncertainty reduce the value of inventions because they do not provide adequate incentives to innovate. We argue that a moderate level of uncertainty leaves room for experimentation and the introduction of inventions that are aligned with — or even trigger — the evolution of the technological trajectory. By contrast, in conditions of low uncertainty, a tendency to develop incremental improvements of existing technology reduces the value of inventions, suggesting a greater importance of path-dependent strategies in these conditions. We believe that these results contribute to a better understanding of the effect of uncertainty in the management of invention. These results are also relevant to the specialised stream of literature that investigates patent value (Harhoff *et al.*, 2003; Gambardella *et al.*, 2008) because they underscore the importance of including environmental factors in the analysis.

We suggest that these findings are important with respect to the literature on the management of invention because they contribute to the untangling of the factors underlying the generation of valuable inventions. The findings reported in this paper shed light on how invention value is affected by both path-dependent and path creating capabilities, and the level of uncertainty of technology. Importantly, we show that even with mature technology, the invention can be the outcome of different strategic patterns.

As with all research, this study has limitations. First, our data permit us to observe only inventions that are patented. We are thus unable to observe capabilities deployed in projects that generated unpatented inventions, for example, those protected by trade secrets or that proved to be unsuccessful and thus were not patented. Similarly, we could not observe the extent to which capabilities developed in failed projects have subsequently underpinned successful inventions. Future studies could pursue a closer investigation of how environmental uncertainty and existing capabilities endowments of firms impact the trial-and-error process of invention and whether the transference of capabilities is related to inventions. Second, our study focuses on single inventions rather than on clusters of inventions that typically give rise to an invention. In other words, we examine the values of single patents without considering complementarities with existing or future inventions. Future research could examine the nature of capabilities needed to exploit these complementarities. Such studies could analyse a firm's product portfolio in combination with its patent portfolio. In this study, however, we addressed this effect by including, for each firm, the total number of patents pertaining to hydrocracking and by measuring firms' degrees of specialisation at a particular point in time. With respect to the empirical measures, the classification of technological capabilities in this study relies on IPC codes. These codes are attributed to patents by examiners of patent offices and thus are prone to some degree of subjectivity. Although the use of such codes is standard in patent studies, we validated and improved the measure by discussing their use with technical and patent experts with substantial experience in this technology.

We restricted our analysis to a single technology employed in a single industry, raising the issue of the generalisability of our findings. Other industry settings that include a new technology or product area, such as cellular phones or genetically modified foods, might exhibit different returns for the relative rarity of invention. Additionally, the level of competition in an industry could also affect both patenting behavior and the returns for patent protection. The empirical setting used in this study resembles a broad level of competition among heterogeneous actors, and, in the case of oligopolistic or monopolistic competition, the results could be different. Thus, further research could address other technologies applied in different industries and in different stages of their life-cycle.

Despite these limitations, we believe that this paper provides a worthwhile contribution to the academic debate regarding path-dependence in management of innovation and that the study offers important insights for firm management. Managers may be interested in our finding that widespread capabilities — which arguably require less investment and time to be deployed compared with firm-specific capabilities — may contribute to the value of an invention to the same extent as rare capabilities. Managers should also consider the external forces that affect the development of a technological trajectory, in particular, environmental uncertainty. We find that the predictability of the environment lowers the expected value of invention, which requires managers to carefully assess investment in the development of rare capabilities.

References

Aghion, P and P Howitt (1998). On the macroeconomic effects of major technological change. In *General Purpose Technologies and Economic Growth*, E Helpman (ed.), pp. 121–144. Cambridge, MA: MIT Press.

Agogué, M, P Le Masson and D Robinson (2012). Orphan innovation, or when path-creation goes stale: A design framework to characterise path-dependence in real time. *Technology Analysis & Strategic Management*, 24(6), 603–616.

Ahuja, G, CM Lampert and V Tandon (2008). Moving beyond Schumpeter: Management research on the determinants of technological innovation. *Academy of Management Annals*, 2, 1–98.

Alcacer, J, K Beukel and B Cassiman (2017). Capturing Value from IP in a global environment. In *Advances in Strategic Management*, 36, 165–231.

Araujo, L and D Harrison (2002). Path dependence, agency and technological evolution. *Technology Analysis & Strategic Management*, 14(1), 5–19.

Arora, A and A Gambardella (1994). The changing technology of technological change: General and abstract knowledge and the division of innovative labour. *Research Policy*, 23(5), 523–532.

Arora, A, S Athreye and C Huang (2016). The paradox of openness revisited: Collaborative innovation and patenting by UK innovators. *Research Policy*, 45(7), 1352–1361.

Arthur, WB (1989). Competing technologies, increasing returns, and lock-in by historical events. *The Economic Journal*, 99, 116–131.

Arthur, WB (1990). Positive feedback and the economy. *Scientific American*, 262, 92–99.

Artz, KW and TH Brush (2000). Asset specificity, uncertainty and relational norms: An examination of coordination costs in collaborative strategic alliances. *Journal of Economic Behavior & Organization*, 41, 337–362.

Beckett, RC (2015). Entrepreneurial bricolage: Developing recipes to support innovation. *International Journal of Innovation Management*, 20(5), 1–17.

Bergek, A and K Onufrey (2013). Is one path enough? Multiple paths and path interaction as an extension of path dependency theory. *Industrial and Corporate Change*, 23(5), 1261–1297.

Bertoni, F and T Tykvová (2015). Does governmental venture capital spur invention and innovation? Evidence from young European biotech companies. *Research Policy*, 44(4), 925–935.

Billon, A and P-H Bigeard (2001). *Petroleum Refining*. Paris: Technip.

Bingham, CB and J Haleblian (2012). How firms learn heuristics: Uncovering missing components of organizational learning. *Strategic Entrepreneurship Journal*, 6, 152–177.

Bingham, CB, KM Eisenhardt and NR Furr (2007). What makes a process a capability? Heuristics, strategy, and effective capture of opportunities. *Strategic Entrepreneurship Journal*, 1(1–2), 27–47.

Bowen, S (2012). Testing moderating hypotheses in limited dependent variable and other nonlinear models: Secondary versus total interactions. *Journal of Management*, 38, 860–889.

Bowman, C and V Ambrosini (2003). How the resource-based and the dynamic capability views of the firm inform corporate-level strategy. *British Journal of Management*, 14, 289–303.

Butler, JE (1988). Theories of technological innovation as useful tools for corporate strategy. *Strategic Management Journal*, 9, 15–29.

Cantwell, J and A Bachmann (1998). Changing patterns of technological leadership: Evidence from the pharmaceutical industry. *International Journal of Innovation Management*, 2(1), 45–77.

Cheon, A and J Urpelainen (2012). Oil prices and energy technology innovation: An empirical analysis. *Global Environmental Change*, 22(2), 407–417.

Cohen, W, R Nelson and W Walsh (2002). Links and impacts: The influence of public research on industrial R&D. *Management Science*, 48, 1–23.

Cowan, R (1990). Nuclear power reactors: A study in technological lock-in. *Journal of Economic History*, 50, 541–567.

Damanpour, F and M Schneider (2006). Phases of the adoption of innovation in organizations: Effects of environment, organization and top managers. *British Journal of Management*, 17, 215–236.

Danneels, E (2002). The dynamics of product innovation and firm competences. *Strategic Management Journal*, 23, 1095–1121.

David, P (1985). Clio and the economics of QWERTY. *American Economic Review*, 75, 332–337.

David, P (1994). Why are institutions the 'carries of history'?: Path dependence and the evolution of conventions, organizations and institutions. *Structural Change and Economic Dynamics*, 5(2), 205–220.

DiMaggio, PJ and WW Powell (1983). The iron cage revisited: Institutional isomorphism and collective rationality in organizational fields. *American Sociological Review*, 48, 147–160.

Easterby-Smith, M and IM Prieto (2008). Dynamic Capabilities and Knowledge Management: An Integrative Role for Learning? *British Journal of Management*, 19, 235–249.

Eisenhardt, KM and JA Martin (2000). Dynamic capabilities: what are they? *Strategic Management Journal*, 21, 1105–1121.

Ernst, H (2003). Patent information for strategic technology management. *World Patent Information*, 25, 233–242.

Fleming, L (2001). Recombinant uncertainty in technological search. *Management Science*, 47, 117–132.

Fleming, L and O Sorenson (2004). Science as a map in technological search. *Strategic Management Journal*, 25, 909–928.

Fontana, R and M Guerzoni (2008). Incentives and uncertainty: An empirical analysis of the impact of demand on innovation. *Cambridge Journal of Economics*, 32, 927–946.

Gambardella, A, D Harhoff and B Verspagen (2008). The value of European patents. *European Management Review*, 5, 69–84.

Garud, R and P Karnoe (2001). Path dependence and creation. London: Lawrence Erlbaum Associates.

Garud, R, A Kumaraswamy and P Karnøe (2010). Path dependence or path creation? *Journal of Management Studies*, 47(4), 760–774.

Guha, M (2016). Shadows of the past: Path dependence of TV on its sub-systems, complements and substitutes. *Technology Analysis & Strategic Management*, 28(2), 231–249.

Harhoff, D, F Scherer and K Vopel (2003). Citations, family size, opposition and the value of patent rights. *Research Policy*, 32, 1343–1363.

Hall, BH, A Jaffe and M Trajtenberg (2005). Market value and patent citations. *RAND Journal of Economics*, 36(1), 16–38.

Henderson, RM and KB Clark (1990). Architectural innovation: The reconfiguration of existing product technologies and the failure of established firms. *Administrative Science Quarterly*, 35, 9–30.

Kalkuhl, M, O Edenhofer and K Lessmann (2012). Learning or lock-in: Optimal technology policies to support mitigation. *Resource and Energy Economics*, 34(1), 1–23.

Lai, H-C, Y-C Chiu, Y-C Liaw and T-Y Lee (2010). Technological diversification and organizational divisionalization: The moderating role of complementary assets. *British Journal of Management*, 21, 983–995.

Lanjouw, JO and M Schankerman (2004). Patent quality and research productivity: Measuring innovation with multiple indicators. *The Economic Journal*, 114, 441–465.

Leiblein, MJ (2003). The choice of organizational governance form and performance: Predictions from transaction cost, resource-based, and real options theories. *Journal of Management*, 29, 937–961.

Leonard-Barton, D (1995). *Wellsprings of Knowledge*. Boston, MA: Harvard Business School Press.

Lerner, J (1994). The importance of patent scope: An empirical-analysis. *RAND Journal of Economics*, 25, 319–333.

Luque, A (2002). An option-value approach to technology adoption in US manufacturing: Evidence from microdata. *Economics of Innovation and New Technology*, 11, 543–568.

Makri, M, MA Hitt and PJ Lane (2010). Complementary technologies, knowledge relatedness, and invention outcomes in high technology mergers and acquisitions. *Strategic Management Journal*, 31, 602–628.

Martin, R and P Sunley (2006). Path dependence and regional economic evolution. *Journal of Economic Geography*, 6(4), 395–437.

Mastrogiorgio, M and V Gilsing (2016). Innovation through exaptation and its determinants: The role of technological complexity, analogy making& patent scope. *Research Policy*, 45(7), 1419–1435.

Metcalfe, JS (1998). *Evolutionary Economics and Creative Destruction*, Vol. 1. London: Routledge.

McGrath, RG (1997). A real options logic for initiating technology positioning investments. *Academy of Management Review*, 22, 974–996.

Meyer, M (2000). Patent citations in a novel field of technology: What can they tell about interactions between emerging communities of science and technology? *Scientometrics*, 48, 151–178.

Meyer, U and C Schubert (2007). Integrating path dependency and path creation in a generalunderstanding of path constitution. The role of agency and institutions in the stabilisation oftechnological innovations. *Science, Technology & Innovation Studies*, 3(1), 23–44.

Narula, R (2002). Innovation Systems and 'inertia' in R&D Location: Norwegian Firms and the Role of Systemic Lock-in. *Research Policy*, 31, 795–816.

Nelson, RR and SG Winter (1982). *An Evolutionary Theory of Economic Change*. Harvard University Press.

Nelson, RR (1994). The co-evolution of technology, industrial structure, and supporting institutions. *Industrial and Corporate Change*, 3(1), 47–63.

Onufrey, K and A Bergek (2015). Self-reinforcing mechanisms in a multi-technology industry: Understanding sustained technological variety in a context of path dependency. *Industry and Innovation*, 22(6), 523–551.

Park, NK, UD Park and J Lee (2012). Do the performances of innovative firms differ depending on market-oriented or technology-oriented strategies? *Industry and Innovation*, 19, 391–414.

Ragatz, GL, KB Handfield and KJ Petersen (2002). Benefits associated with supplier integration into new product development under conditions of technology uncertainty. *Journal of Business Research*, 55, 389–400.

Reitzig, M (2006). Valuing patents and patent portfolios from a corporate perspective: Theoretical considerations, applied needs and future challenges. In *The Management of Intellectual Property*, D Bosworth and E Webster (eds.), pp. 293–316. Cheltenham, UK: Edward Elgar Publishing.

Rycroft, RW and DE Kash (2002). Path dependence in the innovation of complex technologies. *Technology Analysis & Strategic Management*, 14(1), 21–35.

Sorenson, O (2000). Letting the market work for you: An evolutionary perspective on product strategy. *Strategic Management Journal*, 21, 577–592.

Song, J, P Almeida and G Wu (2003). Learning–by–Hiring: When is mobility more likely to facilitate interfirm knowledge transfer? *Management Science*, 49(4), 351–365.

Souder, WE, JD Sherman and R Davies-Cooper (1998). Environmental uncertainty, organizational integration, and new product development effectiveness: A test of contingency theory. *Journal of Product Innovation Management*, 15, 520–533.

Stack, M and MP Gartland (2003). Path creation, path dependency, and alternative theories of the firm. *Journal of Economic Issues*, 37(2), 487–494.

Storey, J (2000). The management of innovation problem. *International Journal of Innovation Management*, 4(3), 347–369.

Suarez, FF (2004). Battles for technological dominance: An integrative framework. *Research Policy*, 33, 271–286.

Suzuki, O and DT Methé (2014). Local search, exploration frequency, and exploration valuableness: Evidence from new pharmaceuticals development. *International Journal of Innovation Management*, 18(2), 1450014.

Sydow, J, A Windeler, C Schubert and G Möllering (2012). Organizing R&D consortia for path creation and extension: The case of semiconductor manufacturing technologies. *Organization Studies*, 33(7), 907–936.

Teece, DJ (2007). Explicating dynamic capabilities: The nature and microfoundations of (sustainable) enterprise performance. *Strategic Management Journal*, 28, 1319–1350.

Teece, DJ, G Pisano and A Shuen (1997). Dynamic capabilities and strategic management. *Strategic Management Journal*, 18, 509–533.

Trajtenberg, M (1990). A penny for your quotes: Patent citations and the value of innovations. *RAND Journal of Economics*, 21, 172–187.

Tushman, ML and L Rosenkopf (1992). Organizational determinants of technological change: Toward a sociology of technological evolution. *Research in Organizational Behavior*, 14, 311–347.

van Zeebroeck, N and B van Pottelsberghe de la Potterie (2011). The vulnerability of patent value determinants. *Economics of Innovation and New Technology*, 20, 283–308.

Webb, C, H Dernis, D Harhoff and K Hoisl (2005). Analysing European and international patent citations: A set of EPOpatent database building blocks. STI Working Paper 2005/9, Directorate for Science, Technology and Industry, Paris, France. Available at: http://www.oecd.org/sti/35520805.pdf.

Westphal, JD, MDL Seidel and KJ Stewart (2001). Second-order imitation: Uncovering latent effects of board network ties. *Administrative Science Quarterly*, 46, 717–747.

Wiersema, MF and HP Bowen (2009). The use of limited dependent variable techniques in strategy research: Issues and methods. *Strategic Management Journal*, 30, 679–692.

Winter, SG (2003). Understanding dynamic capabilities. *Strategic Management Journal*, 24, 991–995.

Wooldridge, J (2009). *Introductory Econometrics: A Modern Approach*. Mason, OH: South-Western Cengage Learning.

Zhang, JA, S Garrett-Jones and R Szeto (2013). Innovation capability and market performance: The moderating effect of industry dynamism. *International Journal of Innovation Management*, 17(2), 1350004.